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14. ABSTRACT A software prototype for AADA (Affordable Acquisition Decision Aid) has been developed which addresses S&T investments. The system achieves the following goals: the ability to determine near-optimal acquisition strategies in the presence of uncertainty concerning many factors that define an acquisition scenario; the ability to estimate the overall utility of a collection of assets in terms of their mutual cooperation in meeting high-level Navy objectives; the ability to recommend acquisition strategies that employ affordability constraints in conjunction with the above; the ability to assist the user in balancing investments across objectives; a simple database structure in which descriptions of acquisition scenarios are stored; finally, a network-centric user interface for accessing and controlling the functions of the system remotely via a web browser. Thus, we have developed and demonstrated a software system to support affordable acquisition decisions, while addressing uncertainty with respect to expected system performance, system cost, future threats and their impact on future force requirements, as well as uncertainty in future budgets.						
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Affordability Modeling in an Uncertain Environment

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2 Introduction

The results reported herein represent a significant step in developing a decision model and software tool to support affordable Naval acquisition planning in the presence of uncertainty and severely constrained budgets. Navy decision makers are faced with difficult tradeoffs among different technology investments, each promoted by their own subject matter experts. In order to arrive at the right trade-offs it is essential to place each proposed technology investment in the overall context of successfully supporting future Navy missions. We aimed to develop a tool to do just that. In addition, we aimed to help decision makers gain insight into what is fundamentally a complex problem by supporting ‘what-if’ type questions regarding the decisions at hand, such as: “Which technologies do I need to fund in order to satisfy a specific Navy objective with high probability?” or “How should I structure my investments in order to guard against the possibility of a technology failure in a certain high-risk/high-payoff investment?” and, most importantly, “What is a good balanced investment strategy to address the full range of expected future Navy needs?”.

To help answer such questions, we developed a software prototype (called AADA–Affordable Acquisition Decision Aid) which

- supports investment decisions among highly diverse proposed technology investments
- measures future asset performance with respect to a diverse range of high-level Navy objectives
- accounts for technological risks, uncertainty in future objectives and threats, and uncertainty in future budgets
- employs genetic algorithms to determine the utility of future assets by performing near-optimal allocation of assets to objectives

AADA is intended to integrate the outputs of performance models, cost models, and other simulation-based acquisition tools to improve the quality of acquisition decisions, aiming to strengthen Navy warfighting capability while reducing total ownership cost.

We met the following specific objectives:

- We extended the underlying mathematical model with respect to the model resulting from Phase I (see section 3).

- We improved the scope and performance of the optimization algorithms (see section 4).
- We produced a detailed system design plan for a network centric acquisition decision aid and a software prototype to meet this design plan (see section 5).
- We developed several Navy-specific acquisition examples to test the software prototype and to aid in transitioning the research towards a marketable product (see sections 6 and 6.3).

In designing and completing the network centric software prototype, we succeeded in delivering a product that had been originally scheduled for delivery in a Phase II Option. This software prototype has proved valuable in our efforts to demonstrate the benefits of our approach to potential customers.

3 Extensions to the Mathematical Model

In Phase I we had successfully demonstrated how a mathematical model describing the optimal allocation of a fixed collection of assets to targets could be generalized to a model for optimal investment decisions.

In order to more faithfully model realistic acquisition decision processes, we needed to broaden the scope of the mathematical model to encompass the following important concepts:

- We generalized our concept of a ‘target’ to the more general concept of ‘objective’.
- We introduced the concept of scenarios to support acquisition planning for a flexible force structure that can address diverse requirements and, in particular, to better model the fact that in multiple possible future worlds faced by the US Navy, different objectives take on different importances.
- We introduced a capability to model varying degrees of technological risk associated with different investments.
- We introduced a measure for the expected impact on Total Ownership Cost of each investment when successfully deployed.

In the following, the resulting mathematical model is elaborated in detail.

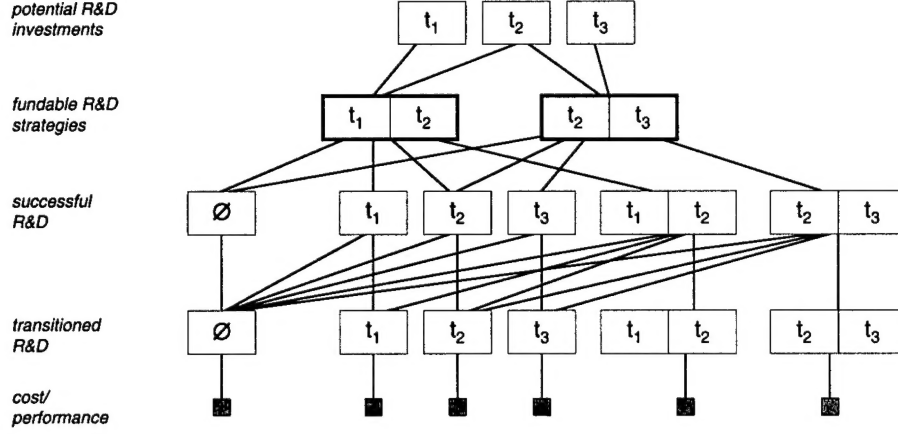


Figure 1: Investment Evaluation

3.1 Detailed Mathematical Model

Given an available budget B and a choice of n S&T investments $I = \{t_1, t_2, \dots, t_n\}$, each with a proposed budget b_i , choose an S&T strategy, defined as a subset $S \subseteq I$, such that the expected S&T cost/performance $cp_S(S)$ is maximal under the constraint

$$\sum_{t_i \in S} b_i \leq B.$$

S&T cost performance (detailed in the following) accounts for uncertainty of S&T results and the impact of successful S&T on asset properties such as predicted effectiveness in achieving multiple objectives, predicted risk while engaged in achieving those objectives, and predicted TOC.

Given a fixed S&T strategy $S = \{t_1, t_2, \dots, t_m\}$, and a probability p_i of success for each such investment, the potential results of that strategy are all the subsets $R \subseteq S$, each with probability

$$p(R) = \left(\prod_{t_i \in R} p_i \right) \cdot \left(\prod_{t_i \notin R} (1 - p_i) \right),$$

so that the cost/performance of strategy S is expressed as

$$cp_S(S) = \sum_{R \subseteq S} p(R) cp_R(R),$$

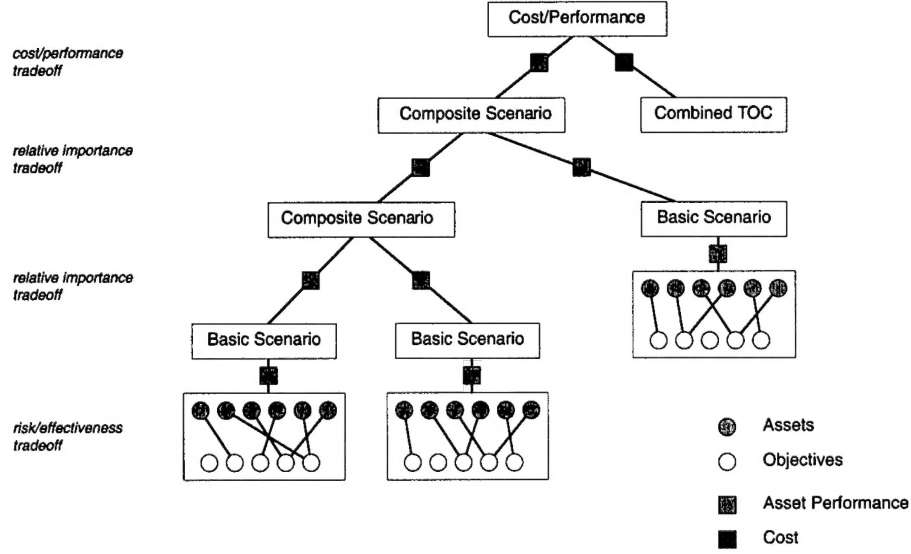


Figure 2: Asset Evaluation

where $cp_R(R)$ is the predicted cost/performance of assets after successfully completing exactly those S&T programs contained in R .

Given an S&T result $R = \{t_1, t_2, \dots, t_j\}$, i.e., a set of successful S&T programs, we expect to transition the results of those programs in order to improve the cost/performance of existing assets. In some circumstances, however, we may choose to fund multiple complementary high-risk S&T programs merely to maximize the likelihood for at least one of them to succeed. Should more than one succeed, it may not be advantageous to transition all of the successes. We therefore define the cost/performance of S&T results as follows

$$cp_R(R) = \max_{T \subseteq R} cp_T(T)$$

where $cp_T(T)$ is the predicted cost/performance of assets after transitioning exactly those successful S&T programs contained in T . Figure 1 depicts the complete subset structure of possible investments and potential outcomes to be evaluated.

When evaluating a collection $T = \{t_1, t_2, \dots, t_k\}$ of successfully transitioned S&T programs, we measure the cost/performance of T in terms of its impact on a collection of existing assets $A = \{a_1, a_2, \dots, a_l\}$. In particular, the following

parameters are considered:

$eff_T(a_i, o_j)$	effectiveness of asset a_i vs. objective o_j
$rsk_T(a_i, o_j)$	risk of deploying asset a_i vs. objective o_j
$toc_T(a_i)$	annualized Total Ownership Cost of asset a_i

We define the resulting TOC change Δtoc as

$$\Delta toc = 1 - \left(\sum toc_T(a_i) \right) / \left(\sum toc_\emptyset(a_i) \right),$$

i.e., as a relative improvement compared to the status quo.

Now the combined cost/performance of T is defined as the weighted sum of cost improvement and predicted asset performance

$$w_{toc}\Delta toc + w_{perf}perf_T(A, H)$$

for a suitable choice of weights w_{toc} and w_{perf} and a suitable performance measure $perf_T(A, H)$ of upgraded assets versus a hierarchy H of anticipated objectives.

Asset performance is measured with respect to a mix of scenarios, defined in a hierarchy (see figure 2). At each level H of the scenario hierarchy with subordinate scenarios H_1, H_2, \dots, H_n , the overall scenario performance is expressed as a weighted sum of individual scenario performances,

$$perf_T(A, H) = \sum w_i p_{H_i} perf_T(A, H_i)$$

for a suitable choice of relative scenario importances w_i and conditional probabilities p_{H_i} of encountering scenario H_i within scenario H .

A basic scenario K is defined in terms of the relative importances it assigns to individual objectives o_1, o_2, \dots, o_k . Denote scenario-dependent objective importance as $imp_K(o_j)$. Denote asset importance for assets a_1, a_2, \dots, a_k as $imp(a_i)$. Asset performance with respect to such scenarios is determined by allocating individual assets to objectives so as to maximize the effectiveness in achieving objectives while minimizing risk. An asset allocation is denoted as a mapping f where $f(i) = j$ when asset i is allocated to objective j . Multiple assets may be allocated to one objective to increase the likelihood of achieving that objective.

We now define the risk component for an asset allocation f with respect to scenario K :

$$rsk_{K,f} = \sum_i rsk_T(a_i, o_{f(i)}) imp(a_i).$$

The effectiveness component must account for diminishing returns when allocating multiple assets to the same objective:

$$eff_{K,f} = \sum_j \left(1 - \prod_{f(i)=j} (1 - eff_T(a_i, o_j)) \right) imp_K(o_j).$$

Now we can express asset performance with respect to a basic scenario as

$$perf_T(A, K) = \max_f (w_e eff_{K,f} - w_r rsk_{K,f})$$

for suitable weights w_e and w_r for effectiveness and risk, respectively. This concludes the elaboration of performance evaluation.

4 Optimization Methods

4.1 Background

A special strength of our work has been the ability to make use of MAAPtm, a Prometheus technology for optimizing the allocation of assets to threats based on expert knowledge of operational parameters of assets and characteristics of threats. MAAP is an automated decision aid developed for the Air Force to help automate the real-time allocation of aircraft to targets (hence the acronym MAAP – Military Aircraft Allocation Planner) in an optimal or near-optimal manner. MAAP is readily customizable for a broad class of allocation problems and has been demonstrated to operate effectively on large problems (400 assets by 400 targets). MAAP combines EDMtm, the Extended Dependency Model originally developed by the Principal Investigator to measure the effectiveness of the Trident Command and Control System [3], with a genetic algorithm (GA)-based optimization engine. This optimization engine continues to represent the core of the AADA optimizer.

During Phase II of this project, we further developed this technology to accommodate the extended mathematical model described in section 3. The AADA optimizer has been structured in a hierarchy of layers which successively break up the overall optimization problem into simpler problems. The innermost layer, the Scenario Level Optimizer, draws on the MAAP allocation engine.

4.2 Structure of the Optimizer

The complete list of layers is given in the following (top-to-bottom):

1. S&T Level Optimizer

(a) S&T funding layer

Enumerates the maximal affordable collections of S&T programs, *i.e.*, the sum of their budgets meet the budget constraints and no further programs can be added without violating the budget limit.

(b) S&T uncertainty layer

For each such collection of fundable programs, accounts for the uncertainty in S&T by considering all subsets of successful programs in accordance with the combined probability of the subset.

(c) Upgrade deployment layer

For each collection of successful S&T programs, considers all subsets of resulting upgrades which may now be considered for deployment.

(d) Objective performance layer

For each subset of deployed upgrades, determines its impact on TOC and balances cost against the resulting performance of upgraded assets versus existing threats. Asset performance is measured with respect to each of the scenarios in the objective hierarchy and results are combined in a weighted sum depending upon user specified importance values and probabilities.

2. Scenario Level Optimizer

(a) Asset allocation layer

Employs previously developed Prometheus GA algorithms to rapidly determine near-optimal allocations of collections of assets to objectives.

(b) Objective function

For a given allocation of assets to objectives, determine its overall value.

4.3 Performance considerations

The two most important performance concerns in the present prototype are the performance of the innermost loops and the combinatorial aspects of the outer optimization layer. As for the former, we were able to adapt proprietary Prometheus

algorithms which had already been heavily optimized. To limit the combinatorial explosion in the outer layer, we employed dynamic programming techniques which ensure that any overlap which could result from evaluating subsets (deployments) of subsets (S&T successes) of subsets (funded S&T programs) of a collection of S&T programs considered for funding is avoided.

As a result, the prototype produces a recommended S&T funding strategy for our USW example (see section 6.3) in approximately 30 minutes on a 900MHz AMD Athlon PC running Linux. This example covers 7 scenarios, 10 different objectives, 8 existing assets and 13 potential technology investments.

The most important remaining performance limitation is that the number of individual investments may not get very large. The limit when running on workstation class hardware is about 20 different candidate investments. We expect to push this boundary beyond 100 investments in Phase III.

5 System Design and Prototype Software

A principal accomplishment of this Phase II project has been the completion of a runnable Web-based prototype client/server software system for specifying and running S&T type optimization problems. The client component is completely written in Java and can be run on a large range of platforms, from workstations and desktops to handheld devices and emerging Internet appliances. The server software consists mostly of a C-based optimization package and is presently hosted on a Linux-based server.

5.1 Client

The AADA client software performs two major functions, as described in the System Design Plan (see appendix A.) It serves as an acquisition scenario editor to specify complex acquisition problems and it provides a postoptimization analysis capability to inspect and evaluate system recommendations.

For the first of these functions, the System Design Plan called for three layers responsible, respectively, for defining objectives, existing assets, and S&T programs for developing asset upgrades. In developing the prototype software, we have found it useful to further subdivide the first of these layers and to provide separate layers for specifying basic objectives on one hand and the scenarios assigning importances to those basic objectives (depending on a user-defined context) on the other.

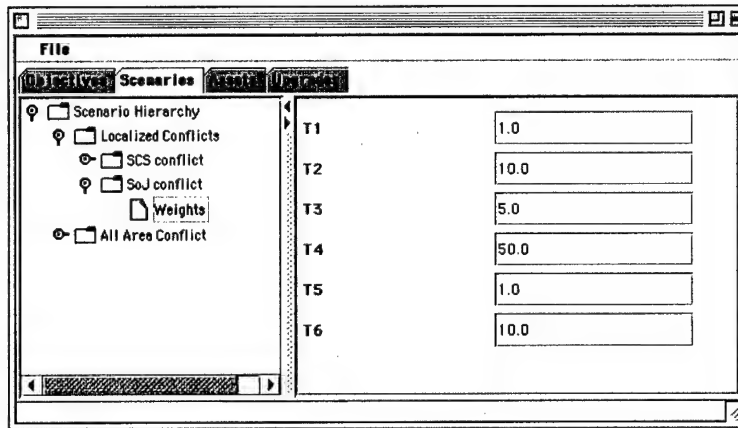
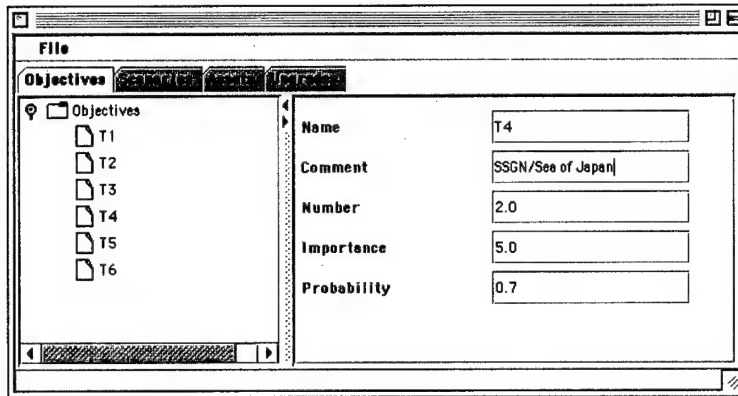


Figure 3: Objective layer (top) and scenario layer (bottom)

In the following, we will illustrate the various layers with screenshots from the initial version of our ASW in the Littoral example (see section 6.1).

Layer I: Objectives. The objective layer (figure 3) permits editing of a list of the future objectives which must be addressed by future assets. Performance of potential asset upgrades is measured with respect to predicted improvements in meeting those objectives. An objective may be, for example, to counter a specific enemy threat, or to perform a specific task.

Layer II: Scenarios. Depending on a given situation, individual basic objectives may become more or less important. Future assets must be sufficiently flexible to

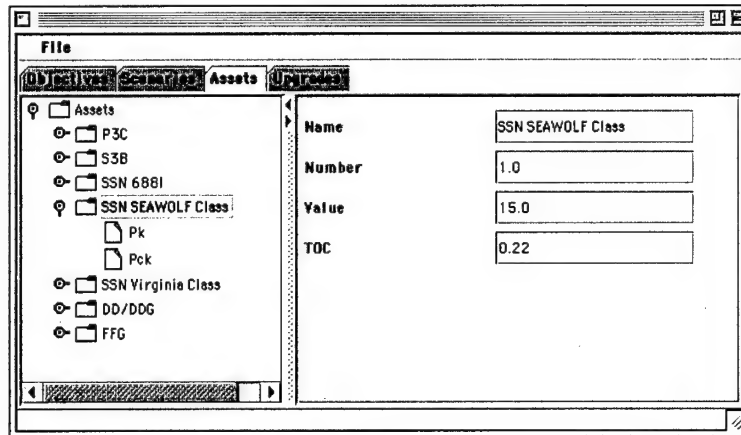


Figure 4: Asset layer

perform in a range of diverse situations. These might include, for example, specific regional conflicts, particular phases in a Naval campaign, or the emergence of a possible but uncertain threat. Scenarios may be nested to any depth so that we could, for instance, specify the phases of a campaign responding to a potential threat emerging during a specific regional conflict. For each scenario, its likelihood and its relative importance, if it occurs, must be specified. All probabilities are conditional with respect to the occurrence of the parent scenario.

Layer III: Assets. Here the user may specify the characteristics of existing assets (see figure 4). For each type of asset listed, the following parameters must be given:

- the number of existing assets of this type
- the value of each asset (measuring the negative impact of losing such an asset relative to other asset types)
- an estimate of present TOC per platform

Of special importance are parameters P_k specifying the degree of success that can be expected when allocating one asset of the given type to each of the basic objectives. During optimization, multiple assets may be allocated to the same objective to increase overall performance. Similarly, parameters P_{ck} specify the likelihood of outright loss of an asset when allocated to each of the basic objectives. P_k and

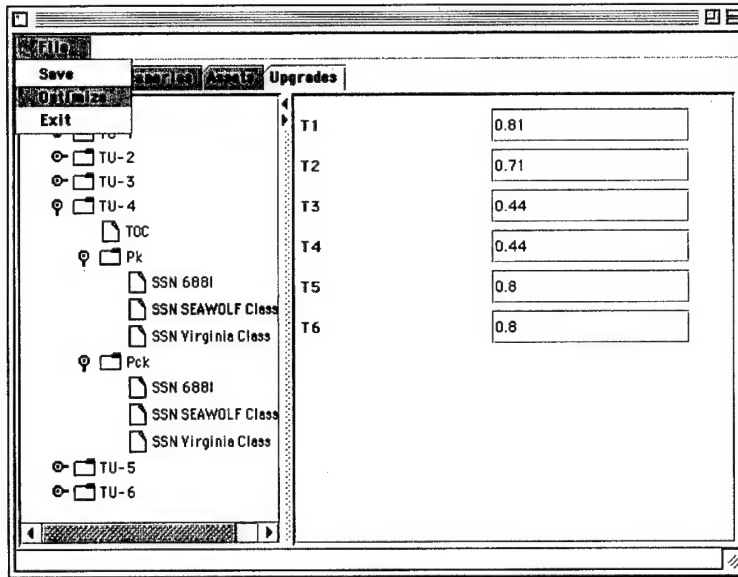


Figure 5: Upgrade layer

P_{ck} are numbers between 0 and 1, with 0 representing 'no impact' and 1 representing 'complete success' or 'certain loss', respectively.

Layer IV: Upgrades. After defining the framework for acquisition decisions in Layers I-III, the range of potential acquisition choices is defined in the upgrade layer (figure 5). Before being able to deploy an upgrade to existing assets, an S&T investment is required. For each upgrade under consideration, the user specifies its S&T cost. Total S&T costs must stay strictly within a fixed budget. S&T does not result in a deployable upgrade with certainty, but with a user-defined probability. When successful, the resulting upgrade is characterized by its effect on asset parameters, in particular, the predicted impact on TOC, P_k , and P_{ck} .

The above four layers together comprise the acquisition scenario editor and allow the definition of complex decision problems. After such a problem has been specified, an 'Optimize' function may be activated from a system menu. This transfers a machine representation of the optimization problem to a server (see section 5.2). The server performs the computations required to determine acquisition recommendations which are transmitted back to the client and presented for postoptimization analysis, described in the following.

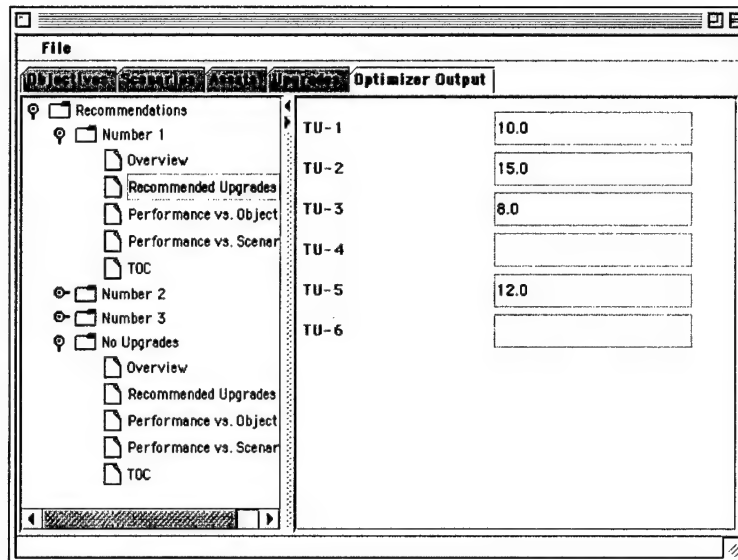


Figure 6: Output layer

Layer V: Optimizer Output. While the previous layers dealt with data entry, the output layer (figure 6) permits reviewing of results. The system presents its top three acquisition recommendations, as well as an evaluation of a hypothetical 'no-upgrade' option, to help visualize projected improvements versus the status quo. An overview screen lists total S&T cost for the proposed upgrades, a measure of the expected overall performance versus the stated objectives, as well as expected overall TOC. A second screen details the upgrades recommended for S&T funding, along with their S&T cost.

5.2 Server

The bulk of the server consists of C-based optimization software structured along the lines described in section 4.2. The interface between the optimization code and the Java client is provided by a small Java package using the Java RMI (remote method invocation) facility. The server also manages access to the AADA system for multiple users. In the short term, this has proven useful for purposes of demonstrating the AADA software to potential customers. In the long term we expect to support multi-user collaboration on complex acquisition decision problems.

6 Navy-specific acquisition examples

Three examples were developed in the course of this program. These examples were used to demonstrate the power and utility of AADA. The first is labeled ASW. The second, an example of programs or exploratory developments to help the Navy deter and counter weapons of mass destruction, is labeled WMD. The third example, called USW, enhances the first by adding new levels of complexity.

6.1 ASW

This first example was used to develop and demonstrate the AADA concept. It is representative of a class of acquisition decisions that program managers regularly encounter. Furthermore this type of problem cannot be solved using linear programming. A genetic algorithm or other non-linear technique is needed. The structure of AADA emerged from this example, which constituted our first prototype.

The context of the problem includes two operational theatres with six threats, or objectives. The asset mix includes air, surface and subsurface ASW platforms. There are six potential technology upgrades, two for each asset class. The problem is to decide which portfolio of technology upgrades within a fixed budget would provide the most performance while minimizing total ownership costs.

A generic description of the problem, its structure, and the relationships of the various factors can be found in appendix B, "Affordable Acquisition Decision Aid (AADA) Descriptive Guide for Analysts."

6.2 WMD

This problem was defined to demonstrate the ability of the AADA process to address one of the four strategic concepts of Submarine Undersea Warfare. Counter and Deter Weapons of Mass Destruction, as a strategic concept, is at a higher level of abstraction than the objective in the ASW example. This example directly addresses concerns faced by the program manager for submarine undersea warfare technologies (NAVSEA93). Therefore, it serves as a demonstration that AADA and its accompanying analytical process can be used to provide structure to a problem area that had been devoid of approaches.

The WMD problem includes chemical, biological and nuclear delivery vehicle threats; near-shore, inland, and shipborne. Two different geographical areas are considered as well as a combined conflict. The assets include Unmanned Aerial

Vehicles (UAV) configured for supporting neutralization of ballistic missiles, unsupported ground surveillance, and signal intelligence; Special Operations Forces with biological/chemical and nuclear delivery vehicle neutralization equipment; Tomahawk Land Attack strike, Anti-Surface Ship strike, and Anti-Ballistic Missile (ABM) missiles; and platform organic signal intelligence.

The effort here showed that AADA can be used successfully at high levels of abstraction. Details of this effort were provided in presentations to ONR, the Undersecretary of Defense for AT&L, and NAVSEA93 Analysts.

6.3 USW

The foundational ASW problem was enhanced with a third operational environment (the Yellow Sea), a new warfare area (undersea mine warfare), and a new class of asset (a joint asset). This new scenario is a combined ASW/Mine/Undersea warfare problem in three operational locations. The asset classes are air (P3, SH-60R), submarine (688I, SEAWOLF, VIRGINIA), surface (DD, DDG, FFG), and coordinated assets. Coordinated assets are combinations of two or more of the previously mentioned platform types. Of thirteen proposed technology upgrades, eight are solely ASW improvements, three are solely mine improvements and two are improvements in both ASW and Mine warfare. Five of these technology upgrades are specific to one type of platform, five are specific to two types and three are applicable to all asset platforms.

These USW enhancements were stimulated by participation at the NDIA Undersea Warfare Conference in September 2000, during which CNO N74 presented an overview of a current Undersea Warfare problem. In this conference multiple presenters reiterated a common acquisition problem:

- There is not enough money to do everything.
- No existing methodology supports balanced investment decision-making and ties it to effects-based mission performance in the field.

Using this scenario, we demonstrate that AADA can provide a balanced set of investment strategies to optimize operational effectiveness across an extremely complex decision problem.

7 Transition Efforts

7.1 ONR

Potential for AADA application to ONR programs has been and continues to be investigated in coordination with the program technical advisor at ONR, Ms. Katherine Drew, Code 362. Two formal briefings and several informal collaborative technical discussions have failed to identify a specific ONR program that has a decision problem that correlates well to the AADA multiple objective tree structure.

7.2 NAVSEA93-SUBTECH

RADM C. Young and his functionary staff (NAVSEA93/NUWC) of the Submarine Technology Office (SUBTECH) were briefed on the benefits of AADA. This briefing and subsequent working sessions with the NUWC SUBTECH technical advisor, Mr. Ron Pikul, resulted from discussions with RADM Young at the Submarine Technology Symposium in April 2000. SUBTECH documents were analyzed and the structure of the decision problem faced by the SUBTECH management office was found to match the structure of AADA. Four follow-up meetings were held, one included a detailed discussion on how AADA would assist the decision makers and described the cost benefits and risk reduction value. Even though the decision analyses are applicable, no funding has been made available in FY2001 to transition the AADA process to SUBTECH.

7.3 CNO-N74-UNDERSEA WARFARE

CAPT G. Ferguson, N74, presented the status of the Navy Undersea Warfare challenge at the National Defense Industrial Association (NDIA) Undersea Warfare Symposium in Groton, CT in September 2000. The decision problem faced by N74 parallels the structure of AADA. The USW example, described in section 6.3, was derived in part as a result of CAPT Ferguson's presentation. Meetings were conducted with N74 personnel (including the Science Advisor, Mr. Barry Raff) and ONR 362 in December 2000. Follow-up meetings were held in January 2001 and the applicability of AADA to assist in the formulation and process for the decisions associated with an Integrated Sponsor Program Plan (ISPP) for Undersea Warfare (USW) was confirmed. Initial funding of \$10K has been identified by the N74 Science Advisor. Discussions with ONR 362 confirmed that additional

funding originating with N74 or a surrogate is necessary to initiate and complete an application of AADA to the USW ISPP problem.

7.4 OUSD-AT&L

Three briefings of AADA to Mr. George Leineweber were held from September through December 2000. Mr. Leineweber understands the decision structure of AADA and its applicability to DoD acquisition programs. He has provided multiple potential contacts and program personnel as candidates for application of the AADA process. Following up with these contacts has to this date not produced a viable funded interest. Mr. Leineweber suggested that the program be briefed to Dr. Paris Genalis, Undersea Programs director for OUSD-AT&L; this will be scheduled during follow-on efforts.

7.5 NAVAIR

Cost analysts within the Naval Air Systems Command (NAVAIRSYSCOM) attended an AADA presentation at the 34th Annual Cost Analysis Symposium (34th ADODCAS) in February 2001. Interest in applying AADA to the acquisition programs for Naval Aircraft was sparked by the mission effects based performance factors used in AADA. The decision faced by these analysts concerns the number and types of aircraft to acquire constrained by a budget with an optimized performance against a variety of threats. No funding has been obtained from NAVAIR as yet, however, discussions will be continued throughout FY01.

7.6 BMDO

The Ballistic Missile Defense Organization (BMDO) cost analysts are also interested in AADA as a result of the 34th ADODCAS briefing. The decision structure faced by BMDO analysts correlates highly with the AADA structure. No progress has been made up to this time in selecting a representative problem from the BMDO office. Follow-up discussions and collaboration are intended.

7.7 OUSD-PA&E

Mr. Steven Miller of the Office of the Undersecretary of Defense, Programs, Analysis and Evaluation, (OUSD, PA&E) requested the AADA team to brief the project at the 34th ADODCAS. This briefing was part of the Advanced Track

AADA Client Demo									
Categories		Scenario Details	Effectiveness		Risk				
T1		Asset	No TU	TU-1	TU-2	TU-3	TU-4	TU-5	TU-6
T2		P3C	0.43	0.50	0.47	0.43	0.43	0.43	0.43
T3		S3B	0.43	0.50	0.47	0.43	0.43	0.43	0.43
T4		SSN 688I	0.65	0.65	0.65	0.40	0.67	0.65	0.65
T5		SSN SEAWOLF Class	0.68	0.68	0.68	0.40	0.71	0.68	0.68
T6		SSN Virginia Class	0.65	0.65	0.65	0.47	0.67	0.65	0.65
		DD/DDG	0.35	0.35	0.35	0.35	0.35	0.45	0.45
		FFG	0.35	0.35	0.35	0.35	0.35	0.45	0.45

Figure 7: GUI design for new AADA client software

training program at the symposium. Mr. Miller was introduced to AADA in December 1999 and has been kept informed of its development on a continuing basis.

At the 34th ADODCAS, Major Robert (Rob) Flowe, USAF, made the observation that a close relationship exists between the AADA process and the Evolutionary Acquisition (EA) process currently espoused by DoD in newly revised acquisition guidance represented in DoD Instruction 5000. AADA readily fits into providing support to the EA decision points and can provide a quantifiable connection to operational effectiveness. Follow-up discussions with Major Flowe and other DoD acquisition professionals will continue in FY01.

8 Follow-On Contract Objectives

After having predelivered a network-centric AADA software prototype (see section 5) that was originally scheduled for completion in a Phase II option phase, we now intend to use the contract replacing the Phase II option to turn this prototype into a more mature and practical form. In doing so, we can draw both on our experiences with setting up and running AADA example applications (see section 6) and on feedback from potential customers and other interested parties to whom we demonstrated the AADA prototype software. The intention is for the software

to become an effective marketing tool in its own right.

This means that most short-term development work will concentrate on improving the AADA front end, *i.e.*, the AADA client software, but also on user documentation which will become easily accessible online. As for the client improvements, the planned new interface will require less navigation in hierarchical tree structures and will display data in tabular form. This will facilitate more convenient data entry and will enable AADA users to keep track of 'the big picture'. A demonstration screenshot of the new interface is shown in figure 7.

The following specific improvements are planned at present:

- make client sufficiently convenient for effective practical use
 - extensive use of tables
 - provide default/guide values for TOC, effectiveness and risk when entering effects of upgrades
 - present input screens as 'forms' generated from a few basic inputs
 - allow copying and pasting of data between AADA and commercial spreadsheets
- provide complete structure editing
 - allow convenient construction of new examples from scratch
 - allow convenient addition and deletion of objectives, scenarios, assets, and upgrades
- make client more transparent to new users
 - provide online help
 - use of 'tool tips' to explain some basic AADA concepts
- enhance AADA functions
 - allow selective 'fixing' or 'blocking' of investments
 - implement colors of money – different budgets for different classes of upgrades
 - automatic basic sensitivity analysis

Appendices

A System Design Plan

A.1 Introduction

This document defines a functional-level design and architecture for the prototype Affordable Acquisition Decision Aid (AADA) software system. The primary goal of this effort is a flexible and extendable decision aid that incorporates the affordability constraints, dependency modeling, and allocation optimization approaches set forth in Phase I of this SBIR effort. Important design goals are:

- The ability to determine near-optimal acquisition strategies in the presence of uncertainty throughout the many factors that define an acquisition scenario,
- The ability to estimate the overall utility of a collection of assets resulting from an acquisition strategy in terms of their mutual cooperation in meeting high-level Navy objectives,
- The ability to recommend acquisition strategies that employ affordability constraints in conjunction with the outputs of the two previous goals,
- A database structure in which scenario-specific and general parametric descriptors of acquisition scenarios are stored,
- A network-centric user interface via which users can access and control all functions of the system.

The second objective will be achieved by simulating, at a manageable level of detail, the operational allocation of potential assets to strategic objectives. In particular, the system will support decisions concerning allocation of Science & Technology (S&T) funds to support future Navy needs. Key functions of the system will include:

- An *acquisition scenario editor* supporting user specification and modification of acquisition options, including
 - quantification of expert inputs

- expected Total Ownership Cost (TOC) of assets to be acquired
 - the nature and structure of objectives to be met
 - the expected performance of assets in achieving those objectives
 - uncertainty in future objectives (e.g., uncertainty as to which future threats will materialize and will need to be counteracted)
 - the technological uncertainty for S&T investments
- An *automatic optimization capability* based on available acquisition options and scenario data defined by the user, resulting in near-optimal acquisition strategies, subject to affordability and viability constraints. Optimality will be with respect to measures of effectiveness (MOEs) which, given a candidate acquisition strategy, will be suprema of user-specified functionals whose parameters come from a database of general and scenario-specific data. Metrics of uncertainty (e.g., low-order moments of their probability distributions) will be associated with the values of MOEs whose functionals include uncertain data.
 - A *postoptimization analysis capability* that will permit
 - viewing of acquisition recommendations
 - querying of reasons behind system recommendations
 - comparison of alternative recommendations, some of which may be defined by the user
 - determination of how the effects of uncertainty about particular parameters in a scenario are manifested in the recommendations

A key property of the system will be network-centric operation. The AADA system will be hosted on remote servers which take heavy processing and storage requirements away from the client side. User interaction with the AADA system will take place through *Commercial Off-The-Shelf* (COTS) technologies like standard Web browsers and, more specifically, XML and Java. Thus, the client software will be compatible with a large number of platforms and configurations, ranging from portable devices to powerful workstations. Multi-user collaboration will be supported by shared access to a centrally managed database which also facilitates system administration and allows future extensions to support automated backup functions and secure access control.

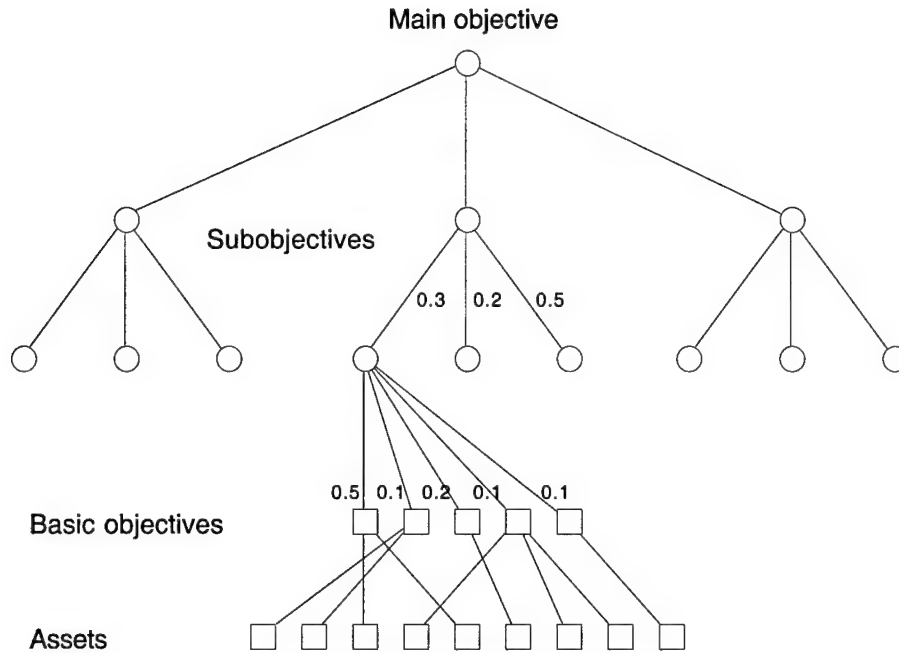


Figure 8: Sample objective hierarchy

A.2 User interface

A.2.1 Acquisition scenario editor

An acquisition scenario will be subdivided into a sequence of three layers of data: projected future objectives, presently available assets, and potential acquisitions. Each layer of data definitions must be completed before entering subsequent layers. Definition of data in each layer will be with respect to data in the preceding layers.

- *Layer I – Projected future objectives.* Definition of future objectives (such as meeting projected future threats) will precede all other data input as objectives will be central in defining future force requirements, which in turn will set the framework for the acquisition process. Two principal interlocking data structures will be provided by the AADA system for defining the nature of future objectives:
 - *The basic objective set.* These will be the basic objectives to which future assets must be allocated. A basic objective might be, for instance,

acquiring Naval superiority in a regional theater of operations. The basic objective set will be the same throughout a given acquisition problem, with the relative weights of individual objectives changing depending on the scenario under consideration.

- *Objective scenarios.* Scenarios may be defined in a hierarchical style in the following way. They may be basic, in which case they will be represented by an allocation of weights to the individual basic objectives, or they may be composite, in which case they will consist of a collection of sub-scenarios, each given a weight to determine its importance with respect to its peers, and a probability of occurrence (which may be 1) given the occurrence of the parent scenario.

Arbitrarily complex objectives can be constructed from these building blocks. A sample objective hierarchy is shown in Figure 8.

- *Layer II – Presently available assets.* Next to the future objectives, assets presently available will be the most important reference point for defining acquisition requirements. Each available asset will be defined in terms of
 1. its TOC, annualized
 2. its probability of achieving a projected basic objective as defined in Layer I above (e.g., probability of kill versus a projected threat)
 3. probability of its loss during assignment (e.g., probability of counterkill)
 4. its importance
- *Layer III – Potential acquisitions.* Potential acquisitions, which will include upgrades of current assets, will be described in terms of the following parameters
 1. deployment cost
 2. degree of improvement provided by acquisition, compared to existing assets
 3. change in TOC to existing assets after acquisition
 4. degree of technological uncertainty (probability of achieving improvement specified above)

In addition, a total budget will be specified as a hard constraint for acquisitions.

Complete layers may be stored and retrieved (to/from a central database), in order to facilitate cooperative development of acquisition scenarios and to allow experimentation, e.g., by varying acquisition options assuming a given definition of objectives and a fixed existing force structure.

A.2.2 Optimization engine

The interface to the optimization engine will be more straightforward than the scenario editor. An initial screen will present the user with the option to redefine default optimization parameters such as

- maximum optimization runtime – the best acquisition strategies found within the runtime limit will be reported
- number of recommendations to be reported back, top-to-bottom
- size of gene population in the genetic algorithm (GA) optimizer
- ratio of genetic recombinations to mutations

A *start* button will initiate the optimization process on the AADA server.

The second screen associated with the Optimization Engine will provide real-time controls, such as

- return to scenario editor, terminating the optimization process
- report partial results, cutting short the optimization process (generally without considering all feasible acquisition options)

Upon completion, the optimization engine will transfer control to the postoptimization analysis tool, starting it off with a high-level view of the top acquisition recommendations.

A.2.3 Postoptimization analysis tool

The postoptimization analysis tool will provide two principal functions, inspection and comparison of acquisition recommendations:

- *Inspection of acquisition recommendations.* Initially, the analysis tool will present a top-level view of the best acquisition recommendations, specifying the subset of potential acquisitions selected along with the total deployment cost. In addition, for each recommendation, the asset performance will be reported both as a whole and with respect to the top-level breakdown into subobjectives. For each such subobjective that is further subdivided into component subobjectives, a button will be provided for displaying performances versus the components and so on, recursively. For each basic subobjective, a button will be provided for displaying the allocation of assets to the corresponding basic objective set. Reported performances will typically include both effectiveness measures and uncertainty metrics.
- *Comparison of acquisition recommendations.* Two alternative recommendations may be compared side by side, highlighting the advantages and the disadvantages of one allocation versus another. Any errors in input that may have caused unreasonable recommendations can be traced to their origin and amended.

A.3 Measure of effectiveness (MOE)

The nature of the MOE for a given choice of acquisition strategy, *i.e.*, its estimated level of performance versus alternative acquisition strategies, will be crucial in defining and understanding the behavior of the AADA system and will be important for predicting the computational requirements of AADA's optimization engine. The AADA MOE will measure acquisition performance versus objectives in terms of likelihood of achieving objectives and expected cost in achieving them. Objectives may be defined as hierarchical structures of subobjectives to any desired degree of complexity. Each subobjective will have a weight defining its importance and will contribute to the parent objective relative to its weight (see figure 8). The MOE computation will be structured accordingly. The overall MOE of an acquisition strategy will be just the degree to which the overall objective will be met by the future assets following the acquisition. For an objective composed of subobjectives, the overall MOE will be a weighted combination of the MOE with respect to each of the subobjectives. For an objective which is not itself composite, the acquisition scenario data will define a set of weights for a fixed set of basic objectives. The AADA system then performs a GA-based optimization to determine near-optimal allocations of future assets to these basic objectives. Based on the predicted performance of individual assets versus individual basic

objectives – and the weights of those basic objectives – the MOE computation will determine the degree to which the objectives are met as whole. It will be possible to associate metrics of uncertainty that characterize statistical distributions with both weights and performance estimates. Thus, we have a complete hierarchical MOE computation composed, ultimately, of a multitude of independent allocation problems involving uncertain parameters.

The total number of allocation problems to be solved will be proportional to the number of subobjectives which are not themselves parents of composite sub-objective nodes. Considering that each subobjective will be defined individually by an AADA user, the increase in computational requirements relative to that of the single allocation case of the Phase I product remains manageable in the sense that there will be no combinatorial explosion introduced by the hierarchy.

A.4 Modular system decomposition and data flow

A data flow diagram is presented in figure 9.

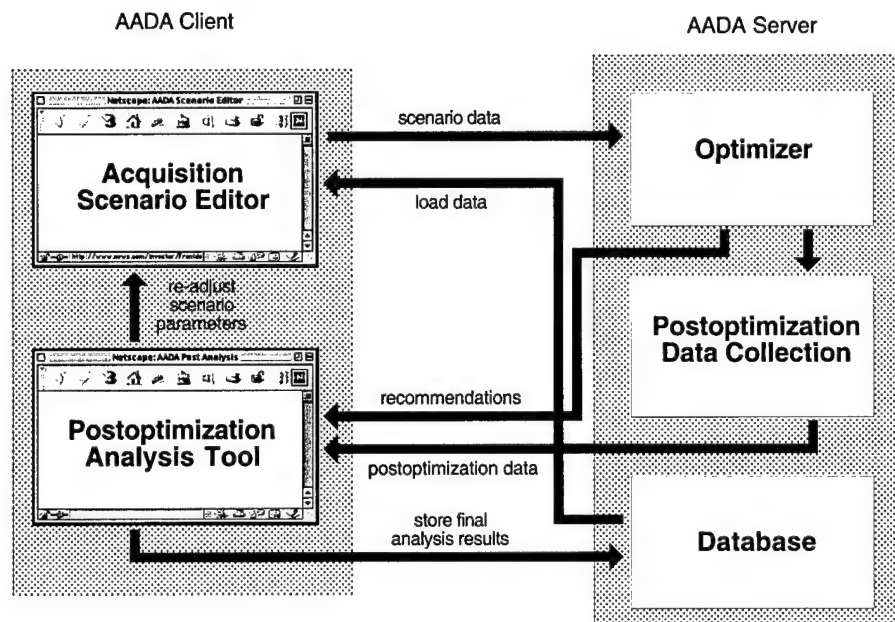


Figure 9: Diagram of AADA system modules and data flow

A.4.1 Client side modules

1. *Acquisition scenario.* This module will process user input to define acquisition scenario data as described in section A.2.1. It will also have access to a central database for storing/retrieving data to be used for revision and experimentation. The data produced by the editor, including control options (see section A.2.2), will become the input for the optimization engine.
2. *Postoptimization analysis tool.* This module will receive run-time status reports from the optimization engine. It will allow detailed review both of AADA recommended and user-defined allocations. A link back to the editor will be provided for the identification and correction of errors, as well as further experimentation. The postoptimization analysis module will have the ability to store the final state of the project to the central database for later revision. The top recommendations and optimization status report may be saved locally, as well as remotely. A hardcopy may also be produced.

A.4.2 Server side modules

1. *Optimization engine.* This module generates near optimal acquisition strategies based on the input data obtained via the acquisition scenario editor. The optimization engine consists of two optimization layers.

The upper layer starts by determining the maximal and feasible acquisition strategies – feasible in the sense that they respect budget constraints, maximal in the sense that no further individual acquisitions can be made without violating those constraints. The filtering of viable acquisition strategies in this sense is shown in Figure 10.

For each such choice, the upper layer determines the expected impact on existing assets, such as improvements to their performance with respect to specific Navy objectives, or TOC improvements.

In order to determine the quality of a given acquisition strategy, the lower optimization layer simulates allocation of the resulting assets (taking into account any improvements) to Navy objectives. This is done by employing a GA-optimization algorithm using the MOE described in Section A.3 as the genetic viability function.

During optimization, this module generates status information for use by the postoptimization analysis tool.

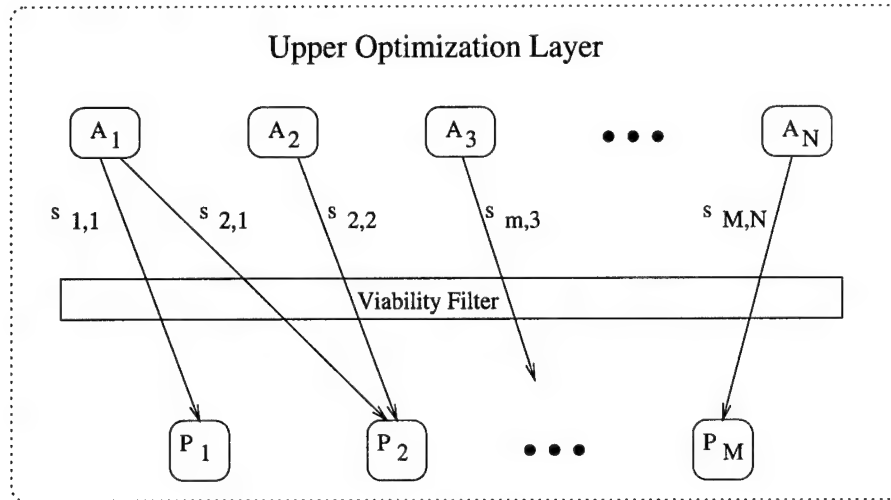


Figure 10: Upper optimization layer

2. *Database module.* This module will store and organize project data for shared access. Data exchange will be performed directly with the client modules.

A.5 System implementation and deployment

The prototype system will be developed on a Pentium-based PC under Redhat Linux. As discussed, user interaction with the system will be entirely via a Web browser. As a result, the client component will be supported by any computer with a Java-capable browser and network access to the server. Parts of the AADA server component will be developed in Java. Other parts will be written in a higher-performance language (C++). The server portion of the prototype system will be readily portable to other UnixTM/Linux platforms and will also be compatible with Windows NT.

B AADA Descriptive Guide for Analysts

Introduction

Class of problem -

Choice of portfolio of near optimal set of investments to accomplish a strategy or set of goals

Methodology - Uses

mathematical model that mimics natural selection to select individual investments that result in optimal or near optimal fitness scores. Fitness

values are established based upon the contextual or environmental criteria. The core of the existing computational aid is a genetic algorithm (GA). The GA aims to breed a selective group of individual investments that produce "offspring" better than the parents.

Analysis - Requires decomposition of the problem into a particular form. The problem set-up is critical to effective use.

AADA is an aid to computation that may need to be modified from its current (8/2000) embodiment of the algorithm to accommodate user unique problems. A generic model and/or building blocks for user assembly and implementation may be available in the future.

Problem type

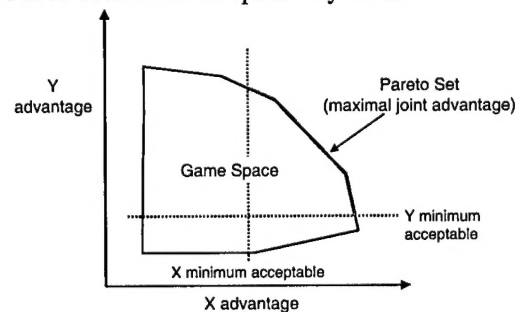
Goals - The computational objective is to obtain Pareto optimality for n investments in an $n-1$ dimensional portfolio space. Pareto optimality is the joint maximal advantage of pairs and because the GA searches for local optimality of groups the results will be near-optimal selection.

Decision characteristics -

AADA in its current embodiment solves multiple criteria decision-making (DM) problems concurrently for multiple objectives and multiple attributes.

Complexity type - AADA solves dynamically complex problems and is an "effects" based model. This is as opposed to Campaign Analysis (CA) models that solve detail complex problems based on attrition.

Knowledge acquisition - A foundation to the solution of any analysis problem is the collection and interpretation of information from subject matter experts. AADA is as subject to the Garbage In - Garbage Out (GIGO) problem as any other computational tool. The research team has identified several valid methods and sources for obtaining



data that has integrity at the precision needed for AADA computations. It is recommended that users consult with the research team to address this pivotal area.

Contextual Definition

Hierarchy - The current AADA structure is rooted in "super goals", vision or ideals such as National Security, hypothesized future worlds or other comprehensive but meaningful high level objectives. Strategic concepts such as those used by the Shell Oil Company or Value (e.g. USAF) based concepts form the highest computationally significant level.

Scenarios - While AADA uses a scenario concept it is not singular as in CA models. Multiple scenarios to the extent needed to adequately reflect the intention of the high level objectives can be defined for AADA computation. Each scenario must be defined in terms of the attributes and measures that are used in the achievement of goals. For example, if accomplishing the high level objectives is based on achieving and maintaining likely superiority in a regional conflict, within a given acquisition cost, total ownership cost and likelihood of success, then these factors must be represented in some cost sink and probability of success information at the lower levels of the problem. This will be illustrated in more detail below.

Core analysis

Mapping and consumption - The GA algorithm requires that when a mapping, i.e. a basic scenario, of resources or assets (RA) to objectives or threats (OT) occurs that for any given mapping the resources or assets are consumed at the required level and cannot be used again in that mapping.

Multiple assignment options - Multiple RA can be assigned to individual OT and vice versa as long as the RA fitness attributes are not completely consumed.

Objectives/threats (OT)

Examples - OT could be individual platforms or sites, regional areas or at whatever level of abstraction that the analyst establishes, as long as they are consistent in scope among one another.

Characteristics and attributes - OT have probability of occurrence, numbers in inventory, lethality (importance), hardness, economic value or similar metrics.

Resources/Assets (RA)

Examples - RA could be the same types of objects as the OT, however, they must be logically mappable to either neutralize or accomplish the respective OT.

Characteristics and attributes - RA have value, numbers in inventory, likelihood of accomplishing the objective for each type of OT, risk in attempting to accomplish the objective for each type of OT, cost of ownership or similar metrics.

Improvements/investments (I^2)

Examples - The investment or improvement portfolio will be made up of whatever the program manager needs to select. These objects must serve to affect the RA characteristics and attributes in a positive (or negative) way.

Characteristics and attributes - I^2 have cost and benefits to the RA characteristics and attributes relative to the OT.

(Near) Optimization

Ideal - The ideal optimization would be the portfolio of investments and improvements that provides the best cost/benefit ratio in absolute terms. Because the individual selections are chosen to be part of a given portfolio in a probabilistic fashion with respect to their fitness the AADA solution will provide "highly fit" individuals but not necessarily "the best".

Choices for real decision-makers - AADA provides candidate portfolios or groups with a measure of fitness to the decision-makers' criteria. It is easy to rerun AADA to establish the sensitivity of the particular problem to variations in input data.

Summary and conclusions

This document is a draft descriptive guide intended to begin the process of knowledge transfer from the research team into the user and application community. At this time early adapting users will need support from the core team because several documented but resolvable issues need to be addressed by the joint user/research community. Given the ease of use of the actual tools and processes, as the knowledge base and user documentation mature it is expected that the AADA tool will be easily employed by analysts with minimal additional training.

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AADA™ is a trademark in the registration process by Prometheus Inc.

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